REPORT DOCUMENTATION PAGE	Form Approved OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*	2. REPORT TYPE	3. DATES COVERED *(From - To)*
31-07-2006	Final	Feb 2004-Apr 2006

4. TITLE AND SUBTITLE	
Determining the Scattering Properties of Verically-Structured Nepheloid Layers from the Fusion of Active and Passive Optical Sensors	5a. CONTRACT NUMBER
	5b. GRANT NUMBER N00014-04-1-0297
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S) Bissett, W. Paul	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Florida Environmental Research Institute 10500 University Center Drive, Suite 140 Tampa, Florida 33612	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) Office of Naval Research 875 North Randolph Street Arlington, VA 22203-1995	10. SPONSOR/MONITOR'S ACRONYM(S) ONR
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT

Approved for Public Release; Distribution is Unlimited

13. SUPPLEMENTARY NOTES

N/A

14. ABSTRACT

See Attached

15. SUBJECT TERMS

Hyperspectral, remote sensing, inversion, inherent optical properties, IOPs, bathymetry, Mine Counter Measures, MCM

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			Beverly Walters
					19b. TELEPHONE NUMBER *(Include area code)* 813-866-3374, ext. 101

Determining the Scattering Properties of Vertically-Structured Nepheloid Layers from the Fusion of Active and Passive Optical Sensors

W. Paul Bissett
Florida Environmental Research Institute
10500 University Center Drive
Suite 140
Tampa, FL 33612

David D. R. Kohler
Florida Environmental Research Institute
10500 University Center Drive
Suite 140
Tampa, FL 33612

Award Number: N00014-04-1-0297

phone: (813) 866-3374 x102 fax: (813) 977-8057 email: pbissett@feriweb.org

http://www.feriweb.org

LONG-TERM GOALS

The optical impacts of a scattering benthic boundary layer are fairly obvious to in situ and remote sensing techniques that measure ocean color. These scattering layers cause an increase in light reflectance from positions above the benthos, a reduction in the penetrating photons to the bottom, and a decrease in photons scattered from the bottom back toward the surface. The net result is that these layers reduce the ability of active and passive optical instruments to retrieve estimates of bathymetry and bottom classification, as well as reduce the abilities of optical Mine Counter Measures (MCM) instrumentation to accurately image the bottom for mine-like objects. These scattering layers are not just optically active, they are in fact acoustically scattering as well. These scattering layers may introduce some real difficulties into both the optical and acoustical methods of detecting mine-like objects, reducing the viability of two major techniques in MCM. The project seeks to assess the spatial extent of these nepheloid scattering layers with active and passive remote sensing techniques, and quantitatively resolve their vertical structure.

OBJECTIVES

1) To assemble simultaneously collected high resolution active (LIDAR) and passive (Spectral Imaging) optical remote sensing data in areas that are impacted by nepheloid scattering layers.

2) To develop the quantitative techniques to resolve the vertical structure of Inherent Optical Properties (IOPs) in the water column from optical remote sensing data.

3) To fuse the active and passive remote sensing data streams to produce digital information products of bathymetry, bottom type, and vertically-structured IOPs.

APPROACH

The use of spectral imagery for classification of benthic properties into information products such as bathymetry and bottom type has a long history in the open literature history (Ackleson, 1997; Dierssen et al., 2003; Lee et al., 1998; Lee et al., 1999; Lee and Carder, 2002; Louchard et al., 2003; Lyzenga, 1978; Maritorena et al., 1994; Mobley et al., 2004; O'Neill and Miller, 1989; Philpot et al., 2004; Philpot and Kohler, 1999; Philpot, 1989; Sandidge and Holyer, 1998; Stumpf et al., 2002). The desire to use spectral imagery instead of more traditional means of estimating this type of information via the use of in-water systems, e.g. bathymetric sounders, multi-beam sonar, and side-scan sonar, stem from the differences in deployment characteristics of the remote sensing and in-water platforms. These differences may be seen in Figure 1, where it is evident that the swath width of the in-water systems decreases substantially as the height of the sensor above the bottom decreases. This means that the effective data or information acquisition rate decreases significantly. In shallow waters less then 5 - 10 m, these systems may be costly, as the drafts of the survey ships are too deep to operate safely requiring the use and coordination of a fleet of small craft. This may just be too cost prohibitive to collect the data, as the time on station may exceed budgetary constraint. In addition to budgetary constraints, the U.S. Navy has operational requirements that may not allow for surface vessels to be exposed in the near shore environment. These "access denied" areas require a mechanism to remotely assess the bathymetry and bottom type, with the benefit of the in water systems.

These budgetary and access constraints have focused a tremendous amount of interest on the capabilities of retrieving marine environmental information from passive spectral remote sensing. Early efforts focused on single or multi-wavelength approaches (Ackleson, 1997; Lyzenga, 1978; Maritorena et al., 1994; Philpot, 1989) that use a form of the two-flow equation (Mobley, 1994) to estimate the bathymetry based upon assumptions about the water clarity and bottom reflectance characteristics. The regression analysis of the predicted bathymetry versus true bathymetry of these early efforts demonstrated admirable results. Yet, frequently there were off-sets in the estimates that were ascribed to environmental errors, including errors in the estimation of water clarity or bottom types. This problem was (is) more specifically related to the need to know the Inherent Optical Properties (IOPs) of the water column, which includes the bottom reflectance, before one could use the two-flow equation in remote areas with little field data or validation.

The shallow water inversion problem in its most general form is the radiative transfer equation. The radiative transfer equation describes the gain and loss of photons along a given path through the interaction equations that govern absorbance, scatterance, and transmittance (Mobley, 1994). The application of the radiative transfer equation to the shallow water inversion problem requires one to simultaneously solve for bathymetry, bottom reflectance, and vertically-structured IOPs when attempting to retrieve an optical reflectance signal (Figure 2). This, of course, was known by earlier investigators, but the number of degrees of freedom (i.e. the number of spectral bands) in the reflectance data was limited in these previous studies, and advancement required working with the available data.

HyperSpectral Imaging (HSI) offers the potential to increase the number of degrees of freedom by which to invert the radiative transfer equation in shallow waters (Lee et al., 1998; Lee et al., 1999; Lee and Carder, 2002; Louchard et al., 2003; Mobley et al., 2004; Mobley et al., 2002; Sandidge and Holyer, 1998). This allows for multiple approaches to resolving the simultaneous variations in bathymetry, bottom reflectance, and vertically-structured IOP. Two of the more common approaches discussed include lookup table approaches that match presolved solutions to the radiative transfer

equation to the HSI and neural network approaches that let the scene or some limited number of presolved solutions train the retrieval algorithm (Philpot et al., 2004). Both of these approaches use computationally intensive processing, which employ the greater degrees of freedom offered by the HSI data, to retrieve a more robust estimate of bathymetry.

There are other optical remote sensing means to accomplish bathymetric soundings. Specifically active airborne remote sensing in the form of LIght Detection And Ranging (LIDAR) has some of the same advantages as the passive HSI (Guenther, 2001; Guenther et al., 2000; Irish et al.), e.g. constant swath over changing bathymetry, as well as some others, such as 24/7 operations and International Hydrographic Office (IHO) Level 1 qualification for bathymetry sounding. The LIDAR bathymetry soundings are less sensitive to IOP variations, and the quality of the data (as recognized by the USACE and IHO) provides bathymetry estimates sufficient for nautical charting. And after nearly 10 years of development, the Naval Oceanographic Office (NAVO) took delivery of the Compact Hydrographic Airborne Rapid Total Survey (CHARTS), which included the latest version of the Scanning Hydrographic Operational Airborne LIDAR Survey (SHOALS). This system provides operational optical sounding from an airborne remote sensing vehicle.

The availability of two optical techniques to retrieve a similar environmental attribute offers the potential for data fusion applications that, at a minimum, can identify geographic areas of high error potential. The comparison of the two sounding estimates may also offer system performance evaluations that help define and refine total data quality. Lastly, the true fusion of the active and passive data stream may yield higher quality estimates of the vertically-structured IOPs, as well as bottom type retrievals. This would provide validation and calibration resources to both data streams, which in turn would provide the highest quality environmental digital mapping products to civilian and military users.

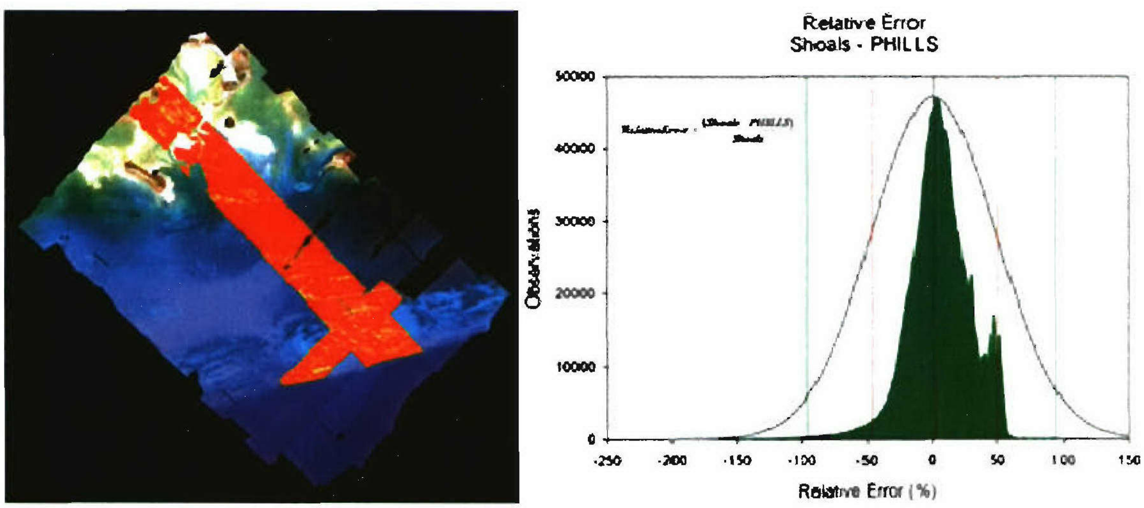

Figure 1. FERI/NRL/NAVO/USACE Joint Hyperspectral/LIDAR Experiment October, 2002. RGB image of the HSI data with SHOALS coverage colored in red (left); The distribution of relative errors between LUT retrieved bathymetry and SHOALS LIDAR bathymetry (right). This represents comparisons of > 1.9 x 10^6 co-located sounding. A Gaussian curve is added to demonstrate the effectiveness of the LUT approach. The distribution or errors is far more centered around zero than would be expected for a normally-distributed population.

WORK COMPLETED – Year 1

In October of 2002, a joint FERI/NRL/NAVO/USACE HSI/LIDAR experiment was conducted off of Looe Key, FL (Figure 1). This experiment yielded high quality HSI data at a 2 m resolution and bathymetric LIDAR data at a 4 m resolution. The joint data set allowed for the advancement and validation of a previously generated Look-Up-Table (LUT) approach to the simultaneous retrieval of bathymetry, IOPs, and bottom type (see Mobley, N0001400D01610001, and Bissett, N000140110201).

During the field experiment, NRL-Stennis and NRL-DC collected in situ Rrs(λ), as well as spectral absorption and scattering with a slow drop optical package. The Rrs(λ) data were used to constrain a tabularized atmospheric correction model (TAFKAA) to correct the HSI data sets. TAFKAA, which was developed by the Naval Research Laboratory (NRL), employs a look up table based correction scheme based on a modification of the Ahmad & Fraser (1982) vector radiative transfer code that was developed by the Naval Research Laboratory (NRL). The TAFKAA code and tables were generated using subroutines from a previously developed atmospheric correction code designed for hyperspectral data (ATREM), and further modified by NRL (Gao et al., 2000). The TAFKAA tables are pre-calculated for a variety of scattering aerosols and atmospheres. Guided by the solar and sensor geometries and environmental conditions, it returns a solution that it applies to the PHILLS2 data set. The sensor and solar geometries are directly derived from the data's time stamp and positional information. The environmental conditions, on the other hand, need to be selected by the user. The parameters that TAFKAA utilizes are: ozone concentration, aerosol optical thickness, water vapor, wind speed, aerosol model, and relative humidity.

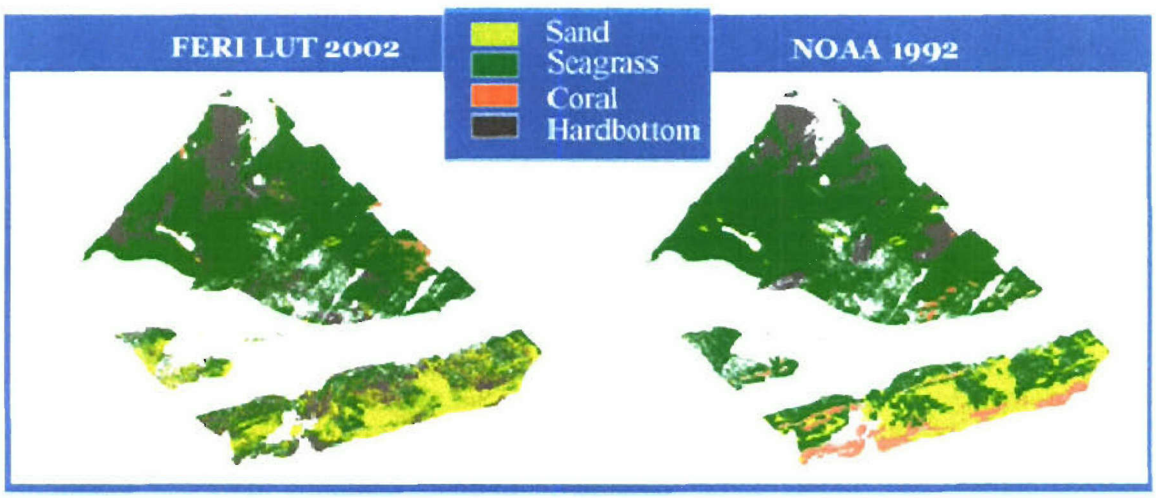

Figure 2. Bottom classification into four types (sand, seagrass, coral,and hardbottom) of the HSI data set (on Left) collected in 2002 and the NOAA NOS/ FMRI data set (on Right) collected in 1992. Missing data from either data set were omitted from the evaluation (white spaces).

RESULTS – Year 1

With the atmosphere properly removed, the HSI image can now be used for advanced algorithm development. We have been developing a radiatively robust method that employs a Look-Up-Table (LUT) of simulated solutions of Rrs(λ) for homogenous, optically clear water columns in tropical

environments. This approach is based on simulating values of Rrs(λ) based on pre-selected water column inherent optical properties (IOPs), bottom depth, and bottom reflectance (Mobley et al., 2002; Mobley and Sundman, 2003). This approach is focused on comparing the calibrated and atmospherically-corrected Rrs(λ) to the LUT's records for every pixel in the image. For each successful match of a LUT record to the spectra, the water type, bottom type, and depth associated with the LUT record was then associated with the PHILLS spectra's location. It is important to note that the library of bottom reflectance spectra used in this exercise was obtained from Bahamian waters and not from the image collection location. In addition, the IOPs were simulated, not measured, demonstrating the ability of this technique to identify and characterize Rrs spectra outside of the calibration/validation region.

The use of SHOALS data allowed us to develop error statistics for the bathymetric retrievals, as well as delineate areas where the LUT algorithm performed poorly, seen as the spike in the distribution of relative errors at the +50% level (Figure 1). This poor performance resulted from an incomplete knowledge of the bottom characteristics. In addition, further study of the error statistics led to the discovery that the ball bearings on the SHOALS scanning mirror were significantly degraded, causing a cross-track error in the SHOALS data of approximately 50 cm. Thus, this LUT approach at separating bottom depth and reflectance from in-water IOPs, particularly if the library of bottom reflectance spectra were obtained locally, may be even better than the data suggests.

The LUT solution also provided estimates of bottom type and IOPs. These bottom type estimates were categorized into 4 categories, Sand, Seagrass, Coral, and Hardbottom, and were matched to the FDGC metadata files from the 1992 NOAA/FWRI photo-survey of the Florida Key (National Ocean Atmospheric Administration National Ocean Services and Florida Marine Research Institute, 2000). Initial results suggested that there appeared to be good overall retrievals for the LUT Sea Grass (Producer Accuracy >85%), but less success with the Coral, Hardbottom, and Sand estimates (Figure 2). In particular, there were significant areas of the reef face that were identified as Sand or Hardbottom, and not as Coral.

The fact that the bathymetry matched fairly well, even if the IOPs and bottom type were not perfect, resulted from the LUT selection algorithm being optimized for bathymetric retrievals. This result is very heartening because it suggests that the approach to HSI bathymetry need not have a perfect IOP and bottom type database in order to retrieve significantly robust bathymetric results. While this is a good result for applications in access denied areas, it does not provide the required accuracy in bottom typing and water quality for civilian resource management.

Fortunately, this was just the first test of this approach, and the LUT database contained only 12,000 entries, owing to the limited vertical resolution and IOP entries. The increased vertical resolution will help reduce bathymetric errors. This will be combined with a much greater distribution of IOPs and will generate a much larger, more representative database for this environment (currently estimated at > 2 million entries). Once the generation of this new database is complete, this analysis will be reconstructed. It is anticipated that this larger database will yield a much more robust HSI/LUT solution for bathymetry, bottom type, and IOPs, as well as even better fusion of the LIDAR/HSI data products. Clearly, these results show the value of coupled data streams in the retrieval of environmental attributes. The fusion of active LIDAR and passive HSI shows promise in the development of new techniques to produce information products for both military and civilian applications.

WORK COMPLETED – Year 2

In 2004, FERI collected hyperspectral imagery Humboldt Bay, CA, which is significantly more turbid than the Florida Keys (Figure 3). During July of 2004, active acoustic bathymetry from multibeam and single beam sonar was collected over the Bay, which will be used for active/passive fusion studies in FY 2006 (Figure 4).

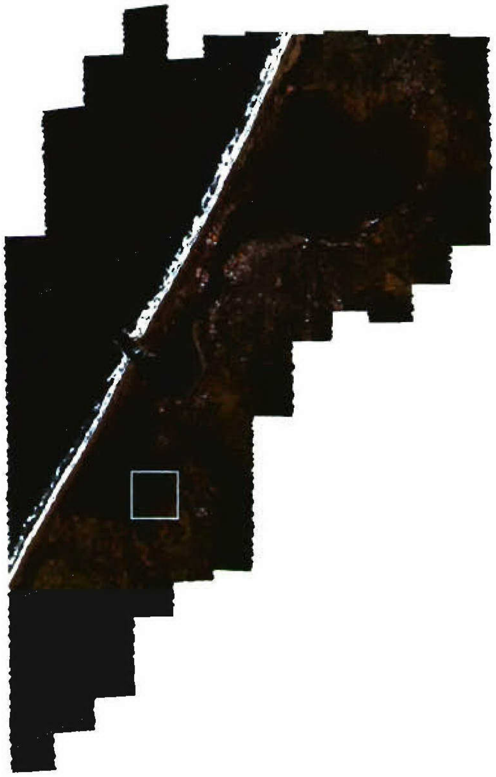

Figure 3. FERI HSI of Humboldt Bay, CA collected October 27, 2004. Multibeam and singlebeam sonar were collected within the entire bay during July 2005.

Results from related projects (Bissett, N000140110201, Mobley, N0001404C0218 and N0001404M0108) suggested that prior expectations of increasing the size of our LUT database (from 12,000 separate spectral Rrs entries to 235,625 entries) would reduce the bathymetric errors. However, contrary to expectation, the bathymetric errors increased with the increase in the number of database entries. This was driven mainly by sensor and environmental noise in the imagery data, as well as database entries that were not representative of the bottom type and water quality of the image location. These results forced us to revisit the spectrum matching selection criteria, with emphasis on using a threshold and other spectral weighting techniques to reduce the bathymetric error rate in the Looe Key imagery.

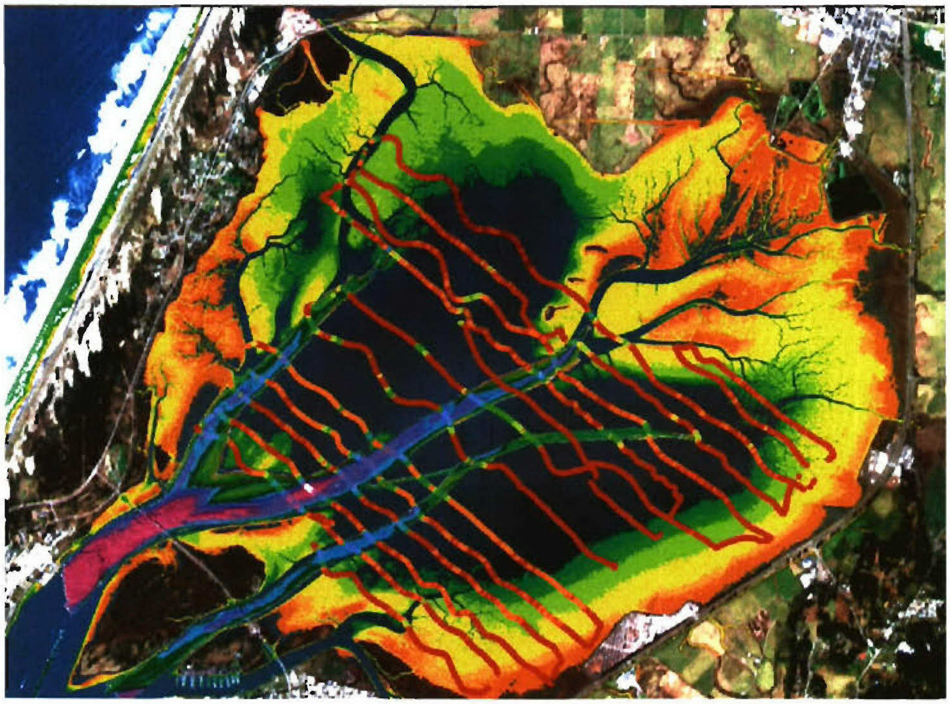

Figure 4. Combined HSI RGB with 2002 topographic LIDAR bathymetry, and 2005 multibeam bathymetry and single beam bathymetry for northern Humboldt Bay.

RESULTS – Year 2

In the current LUT spectral matching, each wavelength is assigned equal importance. RMS error is calculated between the image spectrum and LUT spectrums, and the spectrum with the least RMS difference is chosen as the best match. An inherent problem with this approach is that in hyperspectral remote sensing of coastal environment, the wavelengths that has the most information changes drastically depending on the environmental factors like bathymetry and bottom type. When comparing spectrums for very shallow waters, the wavelengths that contain the most differentiable information are very different from comparing deep water spectrums. For example, the IR wavelengths generally have no information in waters deeper than one meter, while for shallow regions with green bottom, it has the most information. Thus, most of the signal recorded in the IR region for deeper waters is sensor noise and giving equal importance to IR wavelengths in matching can result in high susceptibility to noise. On the other hand excluding the IR wavelengths in matching can result in lower classification accuracy in shallower depths. A mechanism needs to be developed in consideration of the above observations, which can help determine the usefulness of a particular wavelength in spectrum matching.

The approach taken was to try simplistic algorithms first and keep mutating it into more complex ones according to the observations and results. The first method tried was static thresholding. The wavelengths to be used in the matching were predetermined and it remained the same for all the image spectrums. The spectrums were matched only on the wavelengths selected and the rest of the spectrum was ignored. Initially all the wavelengths available were used in LUT matching. The base-level LUT has wavelength range of 400nm-760 nm, and was taken as the initial threshold. Figure 5 shows the absolute depth difference between the depth derived from PHILLS image using the LUT technique and SHOALS image. As seen from the image, the classification error at some places was more than 8 meters. This was considerably worse compared to the classification obtained using the 12K LUT.

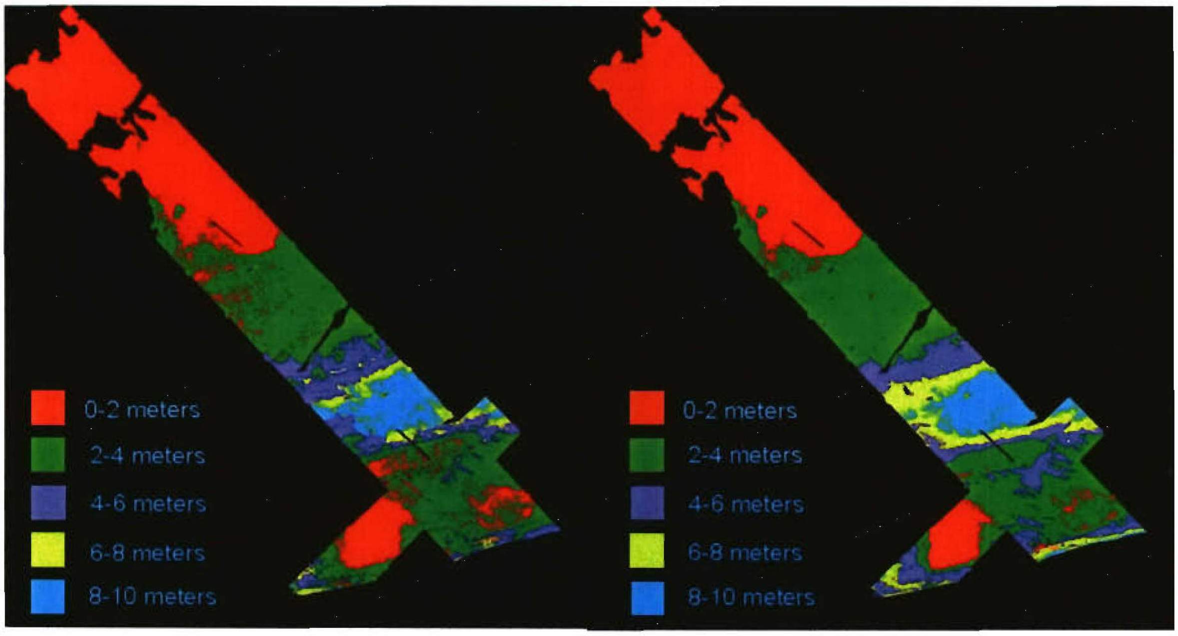

Figure 5. Absolute difference in depths between 200K LUT using static thresholding. (LEFT) Bathymetric errors between LIDAR and HSI LUT estimates using full HSI spectrum to 760 nm. (RIGHT) Absolute difference in depths using static thresholding at 660 nm; note the decrease in errors in the deeper regions of Hawk Channel with the reduce spectral resolution.

As any wavelength beyond 660 would not have any signal, except for very shallow depths, 660 nm was selected as the second threshold. Thus the spectrum was matched only between 400-660 nm wavelengths and rest of the spectrum was discarded. The right Figure 5 shows the classification accuracy by this method. As there was a slight improvement in the classification accuracy by selecting a narrower threshold of 660 nm, the threshold was made narrower until the accuracy started to reduce again. It was noted that when thresholding was done at 575 nm, the classification accuracy was the best on average as shown in Figure 6.

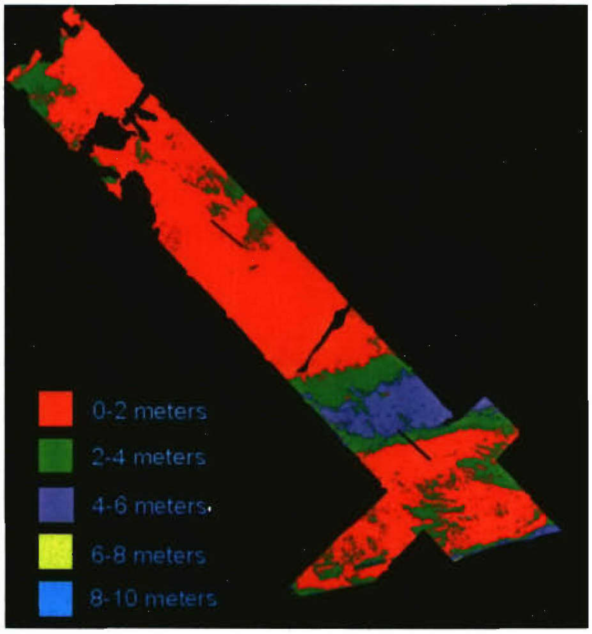

Figure 6. Absolute difference in depths using static thresholding at 575. This wavelength threshold provided the best overall bathymetry match between the LIDAR and HSI LUT using a static threshold.

As seen in Figure 6, thresholding at 575 nm gives good classification accuracy in deeper depths but is significantly worse in shallower depths. This is because shallower depths have a lot of information in the 575-700 nm wavelength range that is ignored in the thresholding. Figure 7 is a plot of few spectrums from the upper left corner of the image where classification accuracy for the image using 575 thresholding was worse then the 660 thresholding image. The figure clearly explains why the 575 thresholding performs poorly at shallow depths. Shallow water spectrums have information between 575 and 660 nm which is completely excluded by thresholding, and thus it retrieves substantially deeper depths. On the other hand, even the 14.25 m deep image spectrum has response in IR wavelengths. This is a result of the sensor and environmental noise. Due to this noise, artificial dark bottoms were retrieved, which forces the underestimation of the depths in classification. Figure 7 shows the bottom selected by both methods. The results confirm the hypothesis that the usefulness of any wavelength in matching two spectrums is a function of the features of those spectrums.

It may be impossible to find a wavelength range that can be used to match all the spectrums. However, it may be possible to use the fusion of active data to more clearly select the appropriate wavelength range for retrieval of bathymetry, bottom type, and water column IOPs. This will allow us to increase the accuracy of our retrievals, while reducing the impact of sensor and environmental noise on the HSI LUT techniques. This will be the focus of our FY 2006 work, with both the Looe Key and Humboldt Bay data.

Work Completed and Results – Year 2 (Addendum, this Grant ended April 2006)

In order to best complete the applied and theoretical aspects of this overall effort (PI Bissett - N000140410297 and PI Mobley N0001404M0108), we decided to divide the labor, with our efforts focused on the analysis of the existing data and the development of the numerical code to rapidly

process HSI imagery. Mobley's effort was to study the theoretical limits of resolving vertical structure in inhomogeneous waters.

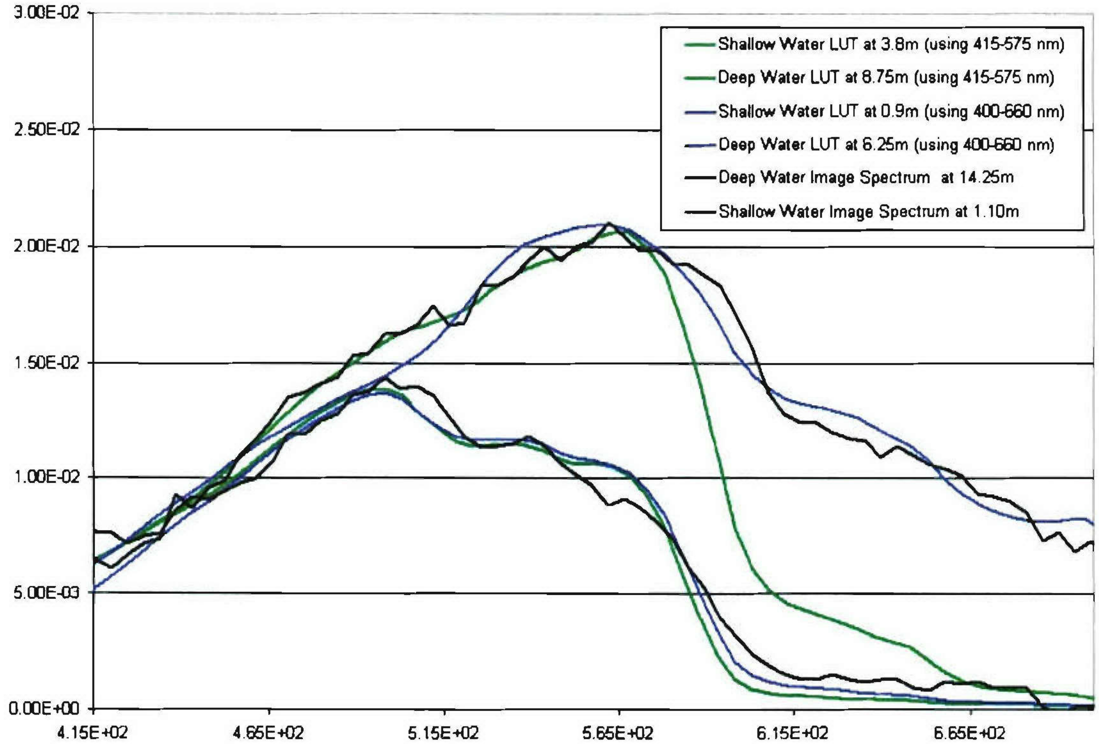

Figure 7. Spectrums plots for regions where static thresholding had considerably low and high classification accuracy. The shallow water (brighter grouping) had better matches using larger thresholds because of the real NIR information in the image spectrum. However, the NIR information was of lower quality in the deeper water, causing significant errors in the larger threshold retrievals.

In the continuation of the application of the current approach into turbid waters, we focused on the southern portion of Humboldt Bay (Figure 3). Our initial LUT generated bathymetric retrieval shows reasonable success at estimating the bathymetry in the bay. These bathymetry estimates were compared against topographic LIDAR data that were collected during a seasonal tide below MLLW. Analysis of these results suggested some of our greatest errors may result from differences in eel grass canopy heights versus bare earth bathymetry (Figure 8), since the eel grass canopy may rise upward to two meters above the bottom (R. Zimmerman, ODU, per. comm.). This introduces an important consideration when fusing multiple remote sensing data streams collected at different time periods. Specifically, how do we deal with transient signals? In this case, we collected the HSI data during the maximum height in the tide, the LIDAR data was collected at the other tidal extreme. The result was that our indications of bottom depth were skewed by the top of the eel grass canopy. Any active or passive sensor operating in these shallow turbid waters would be faced with these same eel grass problem. How one addresses these issues becomes an important part of the analytical product to be delivered to the user community. It also points to the need for confidence intervals to these product estimates, such that these issues and uncertainties are illuminated in the final mapping product.

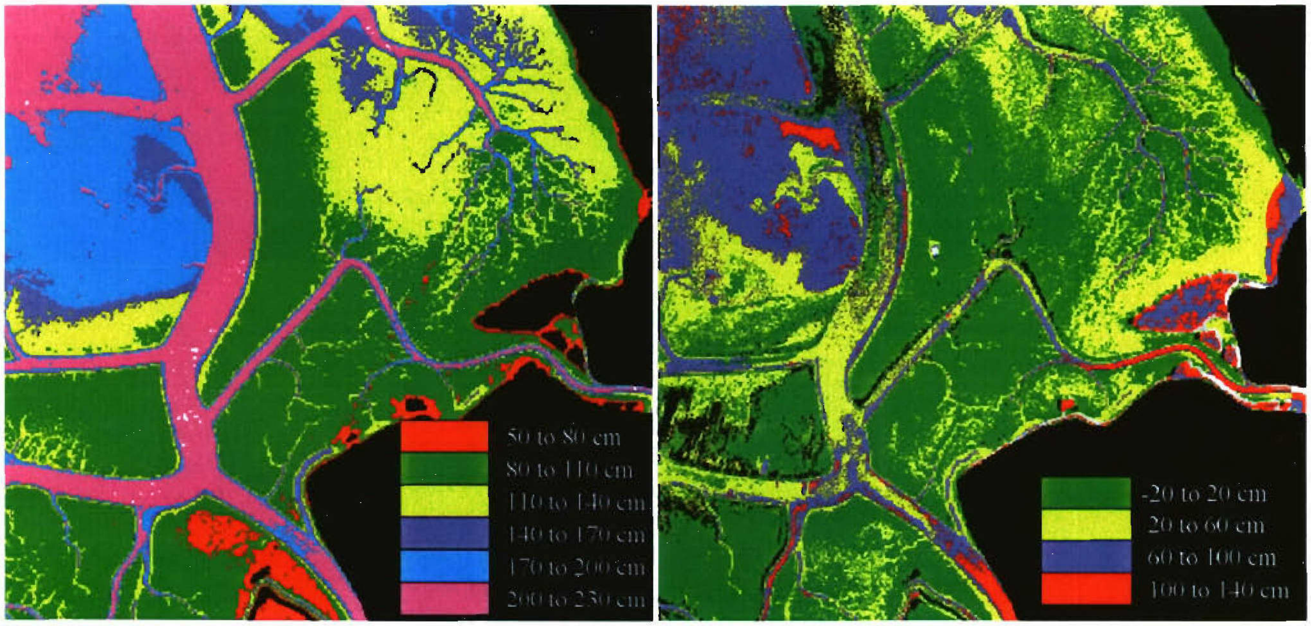

Figure 8. Topographic LIDAR bathymetry estimates (Left) calculated by estimating the tidal height above the MLLW for which this data was collected. The channels in magenta are actually deeper than shown, but the topographic LIDAR system was not able to penetrate the water. Difference between topographic LIDAR estimated bathymetry and LUT estimated bathymetry (Right). Greatest difference is in the NW corner and along channel edges. These regions correspond to high concentrations of eel grass, which may extent upwards to 2 m above the bottom.

In an expansion of the method used in Figure 6 and 7, we began experimenting with a "dynamic threshold" procedure that allowed the spectrum itself to determine the threshold that best suited the reflectance spectrum (seen also in N000140110201). This dynamic threshold approach yielded the results found in Figure 9. The pattern errors still existed, mainly centered in Hawk Channel (errors as high as 6 m), however the relative errors were held below 40% over most of the image. This dynamic threshold procedure appeared to be the best we could do with the PHILLS data set and the single value LUT approach.

At this point we decided to step back and look at this problem from another angle. One of the goals of this effort was to provide not only the ability to look for scattering layers, but also to develop confidence intervals on the solutions found by our inversion methods. This goal required a different perspective, where uncertainty is specifically addressed in the inversion solution. We have begun developing an approach that moves away from thresholding per se, but still allows the data to impart intelligent parameters to the search criteria. The ability to use the HSI data itself, along with the hundreds of thousands (millions) of potential solutions of the theoretical Rrs, provides us with the ability to further optimize the search, while at the same time providing confidence intervals. These results will be discussed in the follow-on program, N00014-06-1-0370.

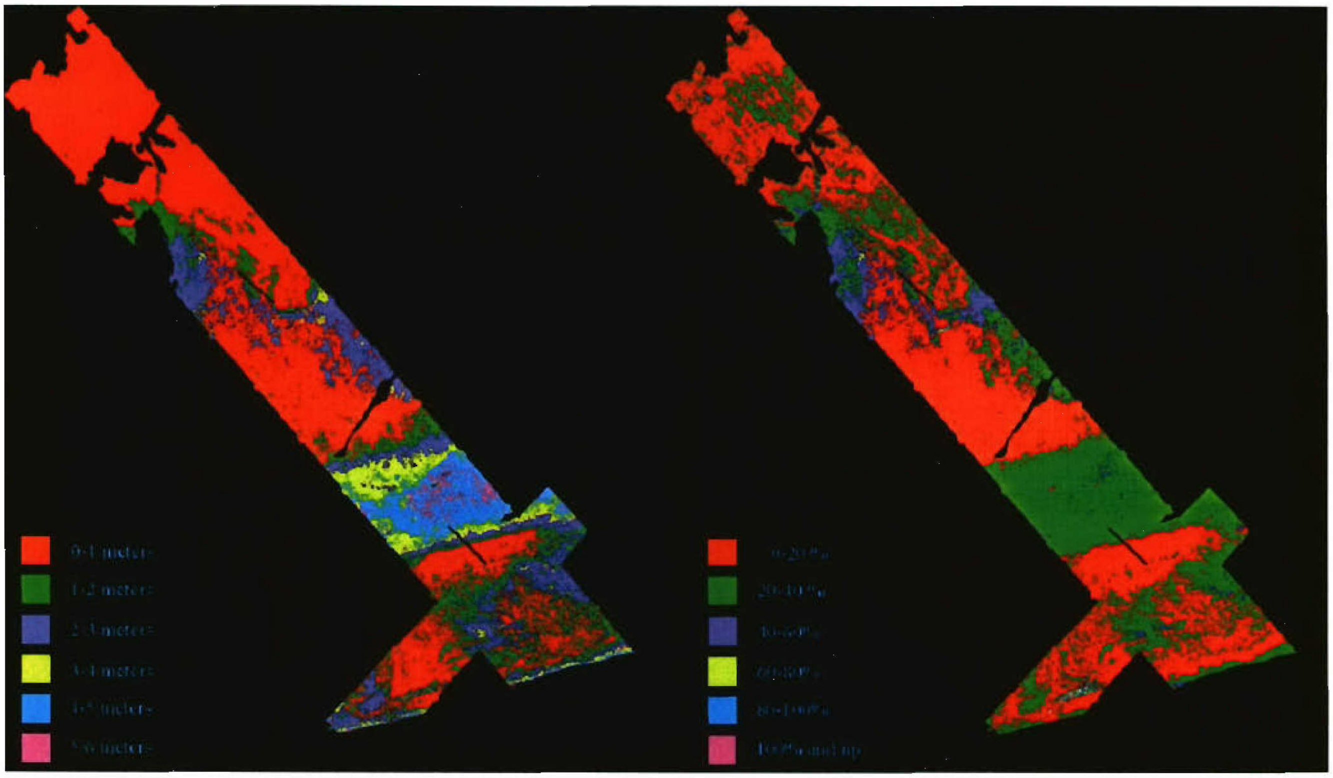

Figure 9. Absolute difference in depths using dynamic thresholding (Left). This dynamic approach to the optimal wavelength threshold provided the best overall bathymetry match between the LIDAR and HSI LUT. The percentage errors are given on the Right.

IMPACTS/APPLICATIONS

This research project is focused on the operational ability to estimate bathymetry, bottom type, target detection, obstacles, visibility, and water column IOPs. This will also include estimates of near bottom scattering layers through the fusion of active and passive optical remote sensing data streams, which may be collected over 100s-1000s of square kilometers per day. In addition to the direct bathymetry, obstacle, visibility, and bottom type products for NSW, this program will provide needed IOP data, and its vertical structure, for the performance prediction of both acoustic and optical MCM detection and identification systems. At the very least, these data will provide the information streams of bathymetry and bottom type, i.e. sand, mud, rock, and clutter, necessary to support current Mine Warfare (MIW) decision aids. The use of hyperspectral sensors deployed on organic UAV platforms, coupled with airborne (e.g. LIDAR) or in-water estimates of bathymetry (e.g. AN/WLD-1(V)1), vertically-structure IOPs (e.g. AUVs), and bottom types, would allow for these information streams to be generated in near-real time in the Littoral Penetration Area.

RELATED PROJECTS

The work is part of a larger project including C. Mobley of Sequoia Scientific, Inc. (N0001404M0108), and it closely interacts with the project led by C. Mobley (N0001404C0218) and PI Bissett (N000140110201).

REFERENCES

Ackleson, S.G., 1997. Diffuse attenuation in optically shallow water: effects of bottom reflectance. In: S.G. Ackleson and R. Frouin (Editors), Ocean Optics XIII. Proc. SPIE 2963, Halifax, Nova Scotia, Canada, pp. 326-330.

Ahmad, Z. and Fraser, R.S., 1982. An iterative radiative transfer code for ocean-atmosphere systems. Journal of Atmospheric Science, 39: 656-665.

Dierssen, H., Zimmerman, R., Leathers, R., Downes, T. and Davis, C., 2003. Ocean color remote sensing of seagrass and bathymetry in the Bahamas Banks by high-resolution airborne imagery. Liminology and Oceanography, 48(1, part 2): 444-455.

Gao, B.-C., Montes, M.J., Ahmad, Z. and Davis, C.O., 2000. An atmospheric correction algorithm for hyperspectral remote sensing of ocean color from space. Applied Optics, 39(6): 887-896.

Guenther, G.C., 2001. Chapter 8. Airborne LIDAR Bathymetry. In: D.F. Maune (Editor), Digital Elevation Model Technologies and Applications: The Dem Users Manual. ASPRS, Washington, DC, pp. 1-69.

Guenther, G.C., Cunningham, A.G., LaRocque, P.E. and Reid, D.J., 2000. Meeting the accuracy challenge in airborne lidar bathymetry, 20th EARSeL Symposium: Workshop on Lidar Remote Sensing of Land and Sea. European Association of Remote Sensing Laboratories, Dresden, Germany.

Irish, J.L., McClung, J. and Lillycrop, J.W., Airborne Lidar Bathymetry: The SHOALS System.

Lee, Z., Carder, K.L., Mobley, C.D., Steward, R.G. and Patch, J.S., 1998. Hyperspectral remote sensing for shallow waters. 1. A semianalytical model. Applied Optics, vol. 37(no. 27): 6329-6338.

Lee, Z., Carder, K.L., Mobley, C.D., Steward, R.G. and Patch, J.S., 1999. Hyperspectral remote sensing for shallow waters: 2. Deriving bottom depths and water properties by optimization. Applied Optics, 38(18): 3831-3843.

Lee, Z.P. and Carder, K.L., 2002. Effects of spectral band numbers on the retrieval of water column and bottom properties from ocean color data. Applied Optics, 41(12): 2191-2201.

Louchard, E., Reid, R., Stephens, F., Davis, C., Leathers, R. and Downes, T., 2003. Optical remote sensing of benthic habitats and bathymetry in coastal environments at Lee Stocking Island, Bahamas: A comparative spectral classification approach. Limnol. Oceanogr., 48(1, part 2): 511-521.

Lyzenga, D.R., 1978. Passive Remote Sensing Techniques For Mapping Water Depth and Bottom Features. Applied Optics, 17(3): 379-383.

Maritorena, S., Morel, A. and Gentili, B., 1994. Diffuse reflectance of oceanic shallow waters: Influence of water depth and bottom albedo. Limnology and Oceanography, 39(7): 1689-1703.

Mobley, C.D., 1994. Light and Water. Academic Press, San Diego, CA, 592 pp.

Mobley, C.D., Bissett, W.P., Bowles, J.H., Davis, C.O., Downes, T.V., Gleason, A., Kohler, D.D.R., Leathers, R.A., Louchard, E.M., Montes, M.J., Reid, R.P. and Sundman, L.K., 2004. Interpretation of hyperspectral remote-sensing imagery via spectrum matching and look-up tables. Applied Optics: submitted.

Mobley, C.D., Sundman, L., Davis, C.O., Montes, M. and Bissett, W.P., 2002. A look-up-table approach to inverting remotely sensed ocean color data, Ocean Optics XVI. Office of Naval Research Ocean, Atmosphere, and Space S&T Department, Santa Fe, NM.

Mobley, C.D. and Sundman, L.K., 2003. Effects of optically shallow bottoms on upwelling radiances: Inhomogeneous and sloping bottoms. Liminology and Oceanography, 48(1, part 2): 329-336.

National Ocean Atmospheric Administration National Ocean Services and Florida Marine Research Institute, 2000. Benthic Habitiats of the Florida Keys, Florida Marine Research Institute Technical Report TR-4, http://sposerver.nos.noaa.gov/projects/benthic_habitats/.
O'Neill, N.T. and Miller, J.R., 1989. On calibration of passive optical bathymetry through depth soundings. Analysis and treatment of errors resulting from the spatial variation of environmental parameters. International Journal of Remote Sensing, 10(9): 1481-1501.
Philpot, W.D., Davis, C.O., Bissett, W.P., Mobley, C., Kohler, D.D.R., Lee, Z.P., Snyder, W., Steward, R.G., Gould, R. and Arnone, R., 2004. Bottom characterization from hyperspectral image data. Oceanography, 17(2): 76-85.
Philpot, W.D. and Kohler, D.D., 1999. Deriving Bathymetry from Hyperspectral Data, IUGG '99, IAPSO Symposium P15: Optical Oceanography & UV Radiation, Birmingham, UK.
Philpot, W.P., 1989. Bathymetric mapping with passive multispectral imagery. Applied Optics, 28(8): 1569-1578.
Sandidge, J.C. and Holyer, R.J., 1998. Coastal bathymetry from hyperspectral observations of water radiance. Remote Sensing of Environment, 65(3): 341-352.
Stumpf, R., Holderied, K. and Sinclair, M., 2002. MAPPING CORAL REEF BATHYMETRY WITH HIGH-RESOLUTION, MULTISPECTRAL SATELLITE IMAGERY, Seventh International Conference on Remote Sensing for Marine and Coastal Environments, Miami, Fl.

PUBLICATIONS

Bissett, W. P., Arnone, R., DeBra, S., Dye, D., Kirkpatrick, G., Mobley, C., and Schofield, O.M. (2005). The Integration Of Ocean Color Remote Sensing With Coastal Nowcast/Forecast Simulations Of Harmful Algal Blooms (HABs). UNESCO Monographs on Oceanographic Methodology- Manual on Harmful Marine Microalgae, UNESCO [submitted, refereed].

Mobley, C. D., L. K. Sundman, C. O. Davis, T. V. Downes, R. A. Leathers, M. J. Montes, J. H. Bowles, W. P. Bissett, D. D. R. Kohler, R. P. Reid, E. M. Louchard, and A. Gleason, 2005. Interpretation of hyperspectral remote-sensing imagery via spectrum matching and look-up tables. *Applied Optics* **44**(17), 3576-3592. [published, refereed]

Schofield, O., Bosch, J., Glenn, S., Kirkpatrick, G., Kerfoot, J., Moline, M., Oliver, M., and Bissett, P. (2005). Harmful Algal Blooms in a Dynamic Environment: How Can Optics Help The Field-Going and Sample-Poor Biologist? UNESCO Monographs on Oceanographic Methodology- Manual on Harmful Marine Microalgae, UNESCO [submitted, refereed].

Bissett, W.P., Arnone, R., DeBra, S., Deterlie, D., Dye, D., Kirkpatrick, G., Schofield, O. and Walsh, J. (2005). Predicting the Inherent Optical Properties and Colored Dissolved Organic Matter Dynamics on the West Florida Shelf. Marine Chemistry, 95, 199-233, [published, refereed].

Glenn, S., Arnone, R., Bergman, T., Bissett, P., Crowley, M., Cullen, J., Gryzmski, J., Haidvogel, D., Kohut, J., Moline, M., Oliver, M., Orrico, C., Sherrell, R., Song, T., Weidemann, A., Chant, R. and Schofield, O., 2004. The Biogeochemical Impact of Summertime Coastal Upwelling on the New Jersey Shelf. Journal of Geophysical Research: 109 (C12S04), [published, refereed].

Chen, R.F., Bissett, W.P., Coble, P., Conmy, R., G. Gardner, B., Moran, M.A., Wang, X., Wells, M.L., Whelan, P. and Zepp, R.G. (2004). Chromophoric Dissolved Organic Matter (CDOM) Source Characterization in the Louisiana Bight. Marine Chemistry, 89(1-4): 257-272, [published, refereed].

Kohler, D.D.R., Bissett, W.P., Steward, R.G. and Davis, C.O., 2004. A New Approach for the Radiometric Calibration of Spectral Imaging Systems. Optics Express, 12(11), [published, refereed].

Mobley, C.D., Stramski, D., Bissett, W.P. and Boss, E., 2004. Optical modeling of ocean waters: Is the Case 1 - Case 2 classification still useful? Oceanography, 17(2): 60-67, [published, refereed].

Oliver, M.J., Kohut, J.T., Irwin, A.J.G., Schofield, O.M., Glenn, S., Moline, M.A., and Bissett, W.P. (2004). Bioinformatic Approaches for Objective Detection of Water Masses. Journal of Geophysical Research, 109(C7): 12, [published, refereed].

Philpot, W.D., Davis, C.O., Bissett, W.P., Mobley, C., Kohler, D.D.R., Lee, Z.P., Snyder, W., Steward, R.G., Gould, R. and Arnone, R., 2004. Bottom characterization from hyperspectral image data. Oceanography, 17(2): 76-85, [published, refereed].

Schofield, O., Arnone, R., Bissett, P., Dickey, T., Davis, C., Finkel, Z., Oliver, M. and Moline, M., 2004. Watercolors in the coastal zone: what can we see? Oceanography, 17(2): 24-31, [published, refereed].

Schofield, O., Bergmann, T., Oliver, M., Moline, M., and Bissett, P. (2004). Inversion of the Bulk Absorption in the Mid-Atlantic Bight and its Utility for Water Mass Analysis in Optically Complex Coastal Waters. Journal of Geophysical Research, 190(C12S04): 12 [published, refereed].

HONORS/AWARDS/PRIZES

2004 Small Business of the Year, Finalist, Florida Environmental Research Institute, W. Paul Bissett, Ph.D., Executive Director, Greater Tampa Chamber of Commerce.

Accomplishments

We have developed the technique to rapidly invert HyperSpectral Imagery (HSI) data into products that include vertical structure in inherent optical properties (IOPs), bottom type, and bathymetry. These techniques include using other data streams (i.e. LIDAR) to constrain the HSI inversion solution. In addition to the direct bathymetry, obstacle, visibility, and bottom type products for NSW, this program will provide needed IOP data, and its vertical structure, for the performance prediction of both acoustic and optical MCM detection and identification systems. At the very least, these data will provide the information streams of bathymetry and bottom type, i.e. sand, mud, rock, and clutter, necessary to support current Mine Warfare (MIW) decision aids. The use of hyperspectral sensors deployed on organic UAV platforms, coupled with airborne (e.g. LIDAR) or in-water estimates of bathymetry (e.g. AN/WLD-1(V)1), vertically-structured IOPs (e.g. AUVs), and bottom types, would allow for these information streams to be generated in near-real time in the Littoral Penetration Area.